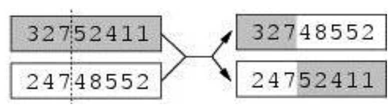
CSE 473

# Lecture 6

(Chaps 4.1 & 5)

# Local Search and Games

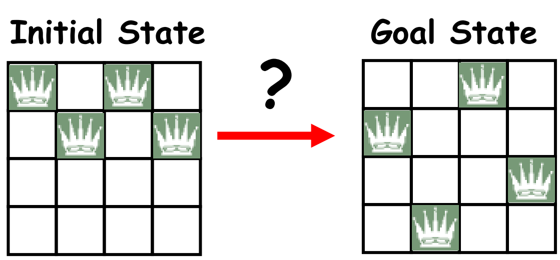




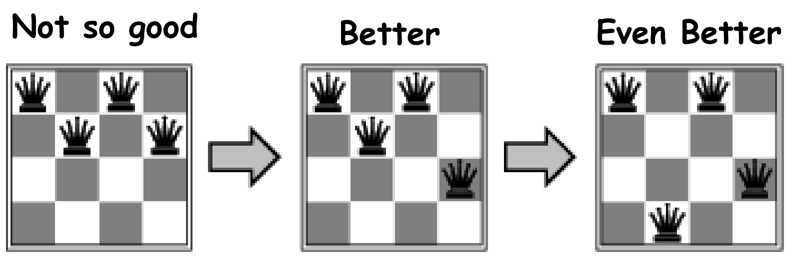

# Local search algorithms

- What if *path* to goal is irrelevant? Only interested in *finding* the goal state !

  E.g., N-queens: Put *N* queens on an *N* × *N* board with no two queens on the same row, column, or diagonal



# Local Search




- Local search algorithms: Keep only a single "current" state and try to improve it
  - Advantage: Very little memory required
  - Also works in infinite (continuous) state spaces

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# Hill-climbing search

"Like climbing Mt. Rainier in thick fog with amnesia"

```
function HILL-CLIMBING(problem) returns a state that is a local maximum
   inputs: problem, a problem
   local variables: current, a node
                    neighbor, a node

   current ← MAKE-NODE(INITIAL-STATE[problem])
   loop do
       neighbor ← a highest-valued successor of current
       if VALUE[neighbor] ≤ VALUE[current] then return STATE[current]
       current ← neighbor
```

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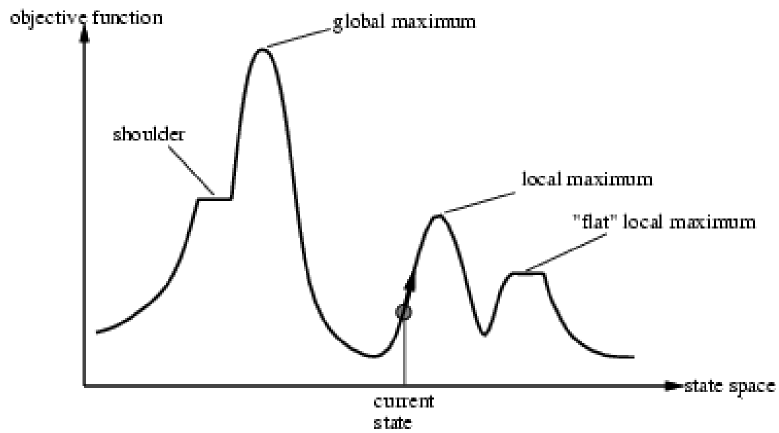
# Hill-climbing search




- Problem: depending on initial state, can get stuck in a local maximum

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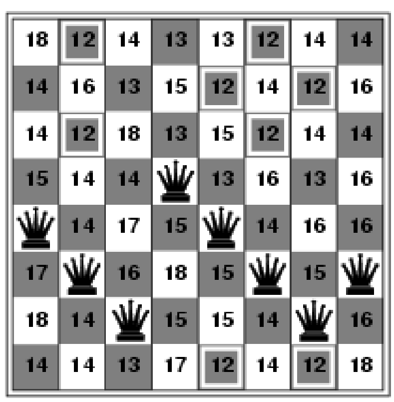
# Example: 8-queens problem

**Objective function *h*?**




*Here,*

*h = 17*

*Numbers denote h-values for available moves*

- *h* = number of pairs of queens that are attacking each other, either directly or indirectly
- Want to *minimize h*

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Queens attacking each other? Most uncivilized. I prefer tea and crumpets.

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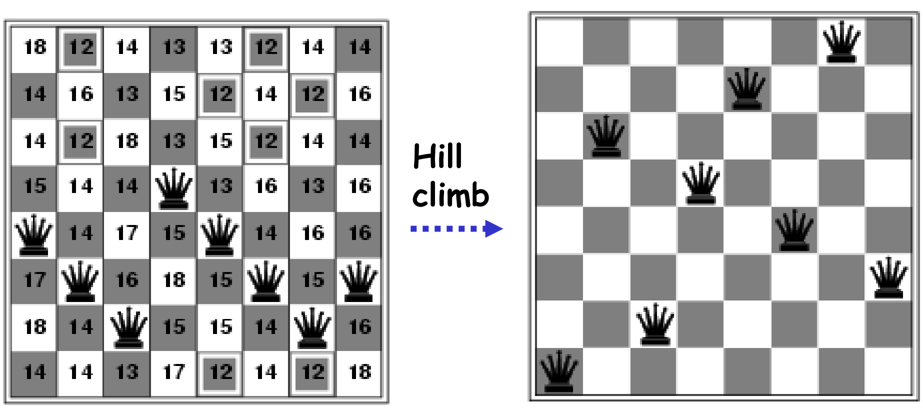
# Example: 8-queens problem




- *A local minimum with h = 1.* Need *h = 0*
- *How to find global minimum/maximum?*

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# Simulated Annealing

- Idea: escape local maxima by allowing some "downhill" moves but gradually decrease their frequency

```
function SIMULATED-ANNEALING( problem, schedule) returns a solution state
   inputs: problem, a problem
           schedule, a mapping from time to "temperature"
   local variables: current, a node
                    next, a node
                    T, a "temperature" controlling prob. of downward steps

   current ← MAKE-NODE(INITIAL-STATE[problem])
   for t ← 1 to ∞ do
      T ← schedule[t]
      if T = 0 then return current
      next ← a randomly selected successor of current
      ΔE ← VALUE[next] – VALUE[current]
      if ΔE > 0 then current ← next
      else current ← next only with probability e^(ΔE/T)
```

- Select random *next*
- Move to it for sure if it has higher value
- Otherwise move to it with some probability

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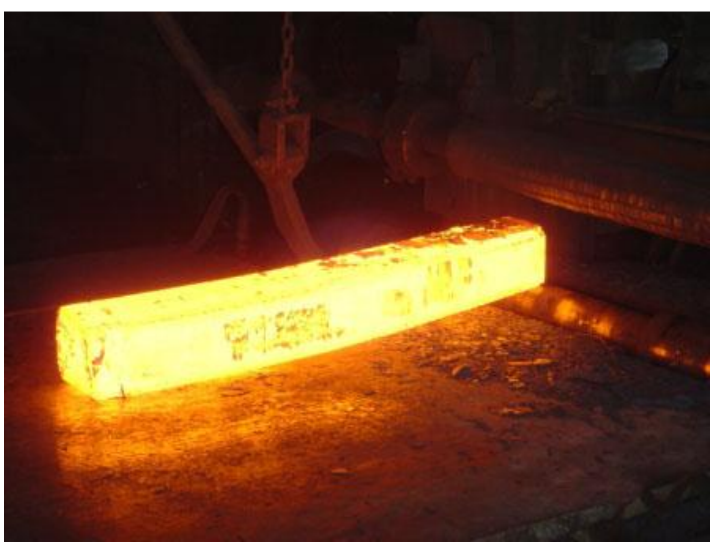
# Why "annealing"?



http://www.kumarsteels.in/process.htm

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# Properties of simulated annealing

- One can prove: If *T* decreases slowly enough, then simulated annealing will find a global optimum with probability approaching 1
- Simulated annealing is widely used for optimizing VLSI layout, airline scheduling, etc.

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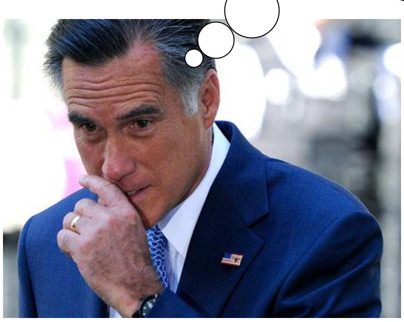
Instead of just one state, what if you keep *multiple current states* (of mind)?



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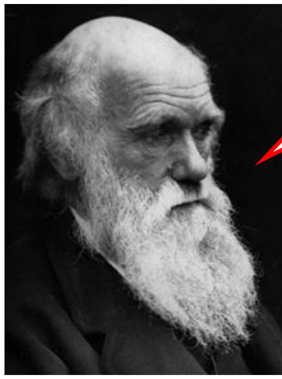
# Local Beam Search

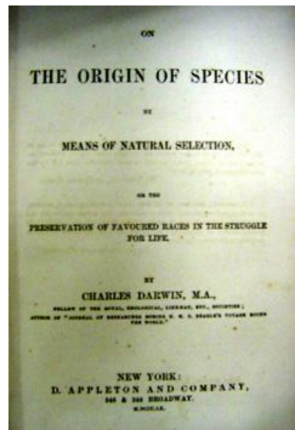
- Keep track of *k* states rather than just one
- Start with *k* randomly generated states
- At each iteration, all the successors of all *k* states are generated
- If any one is a goal state, stop; else select the *k* best successors from the complete list and repeat.



Hey, perhaps sex can improve search?



Sure, venerable lady
– check out my
yonder book.



ON

THE ORIGIN OF SPECIES

BY

MEANS OF NATURAL SELECTION,

OR THE

PRESERVATION OF FAVOURED RACES IN THE STRUGGLE
FOR LIFE.

BY

CHARLES DARWIN, M.A.,

NEW YORK:
D. APPLETON AND COMPANY,
BROADWAY.

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# Genetic Algorithms

- Key idea: A successor state is generated by combining two parent states
- Start with *k* randomly generated states (a population of states)
  - A state is represented as a *string* over a finite alphabet (often a string of 0s and 1s)
- Evaluate strings using a fitness function: higher values for better states
- Produce the next generation of states by selection, crossover, and mutation

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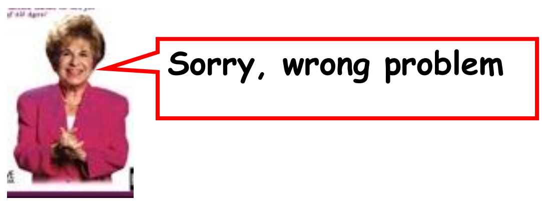
# Example: Evolving 8 Queens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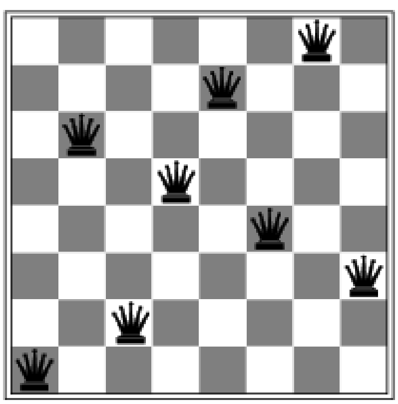
# Example: Evolving 8 Queens



1 6 2 5 7 4 8 3

**String representation of board (read from left to right column): 16257483**

- Need a "fitness function": how "fit" or desirable (i.e., close to the solution) is a string
- Example: number of non-attacking pairs of queens (min = 0, max = 8 × 7/2 = 28)

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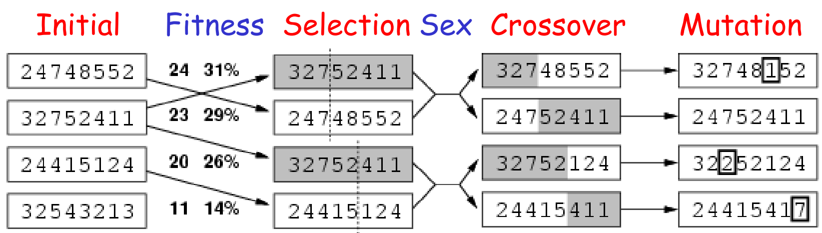
# One iteration of Genetic algorithm




Fitness:

24/(24+23+20+11) = 31% probability of selection for reproduction
23/(24+23+20+11) = 29% etc.

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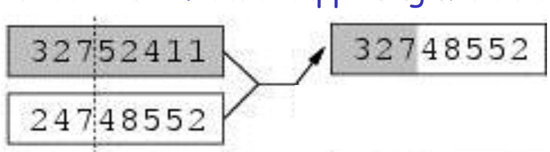
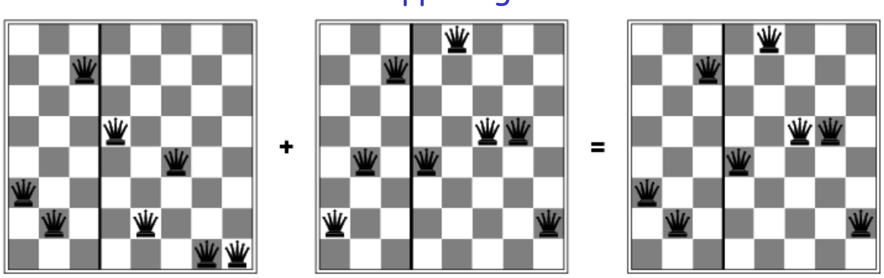
# Queens crossing over

Crossover: What's happening with the strings




What's happening on the board

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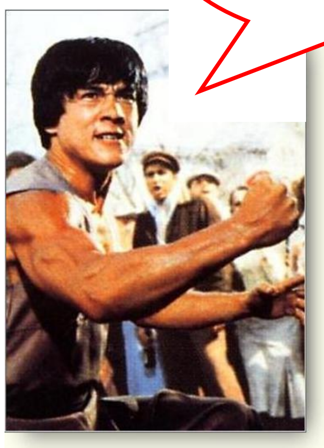
Enough about queens, let's talk about competitive games!



# Adversarial Search

- Programs that can play competitive board games
- Minimax search

Board games?? Lemme outta here!

# Games Overview

| | deterministic | chance |
|---|---|---|
| **Perfect Information (fully observable)** | chess, checkers, go, othello | backgammon, monopoly |
| **Imperfect Information (partially observable)** | battleships | poker, bridge, scrabble |



# Games & Game Theory

- When there is *more than one agent*, the future is not easily predictable anymore for the agent
- In *competitive* environments (conflicting goals), adversarial search becomes necessary
- Class of games well-studied in AI:

  board games, which can be characterized as ***deterministic, turn-taking, two-player, zero-sum*** games with ***perfect information***

# Games as Search

- Components:
  - States:
  - Initial state:
  - Successor function:
  - Terminal test:
  - Utility function:

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# Games as Search

- Components:
  - States: board configurations
  - Initial state: the board position and which player will move
  - Successor function: returns list of *(move, state)* pairs, each indicating a legal move and the resulting state
  - Terminal test: determines if the game is over
  - Utility function: gives a numeric value to terminal states (e.g., -1, 0, +1 in chess for loss, tie, win)

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# Games as Search

Convention: first player is MAX,
2nd player is MIN

- MAX moves first and they take turns until the game is over
- Winner gets reward, loser gets penalty
- Utility values are from MAX's perspective
- Initial state + legal moves define the *game tree*
- MAX uses game tree to determine next move

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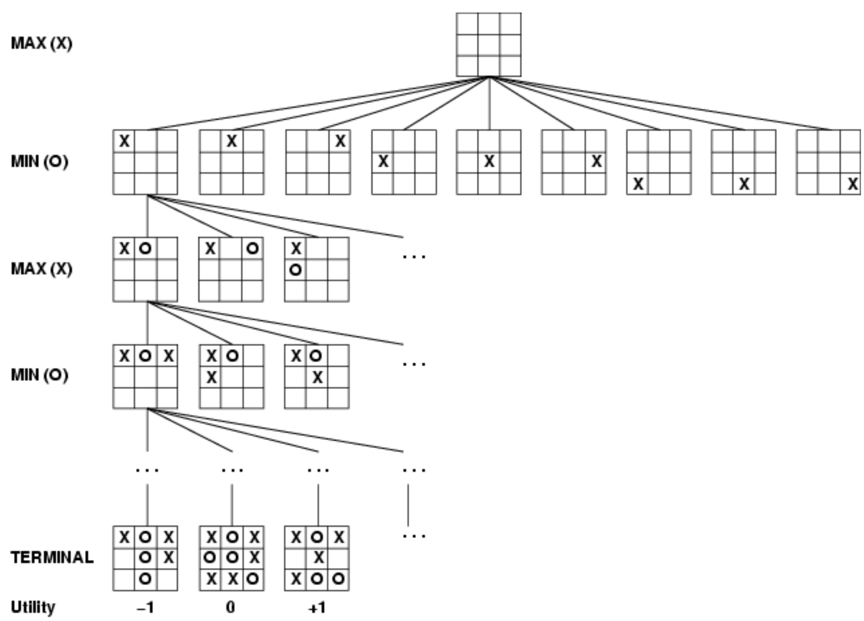
# Game Tree for Tic-Tac-Toe

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# Optimal Strategy: Minimax Search

- Find the *best move* for MAX assuming MIN also chooses *its* best move
- Given game tree, optimal strategy determined by computing the *minimax* value of each node:

MINIMAX-VALUE($n$)=

| | |
|---|---|
| UTILITY($n$) | if $n$ is a terminal |
| $\max_{s \in succ(n)}$ MINIMAX-VALUE($s$) | if $n$ is a MAX node |
| $\min_{s \in succ(n)}$ MINIMAX-VALUE($s$) | if $n$ is a MIN node |

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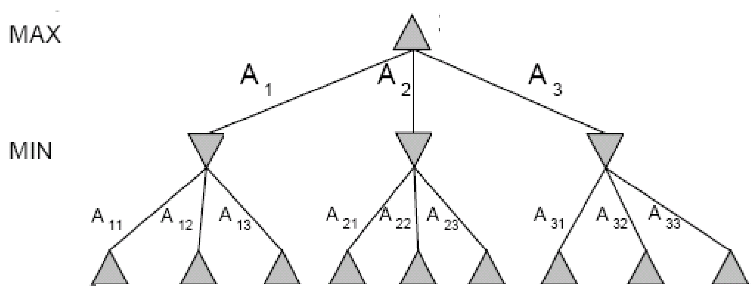
# Two-Ply Game Tree

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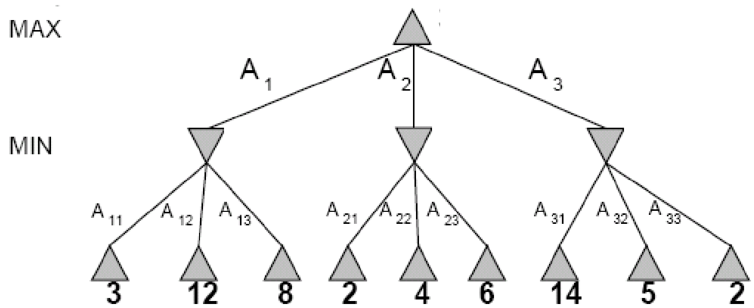
# Two-Ply Game Tree

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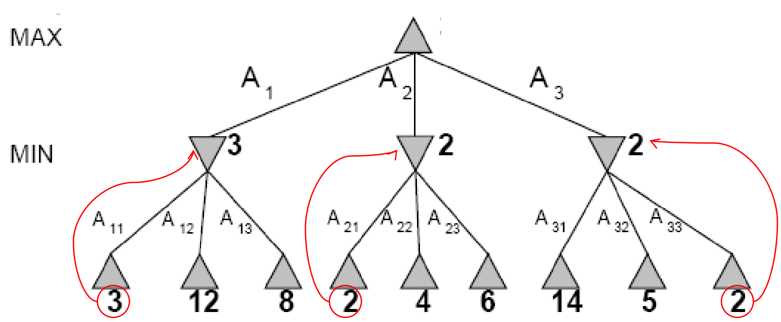
# Two-Ply Game Tree

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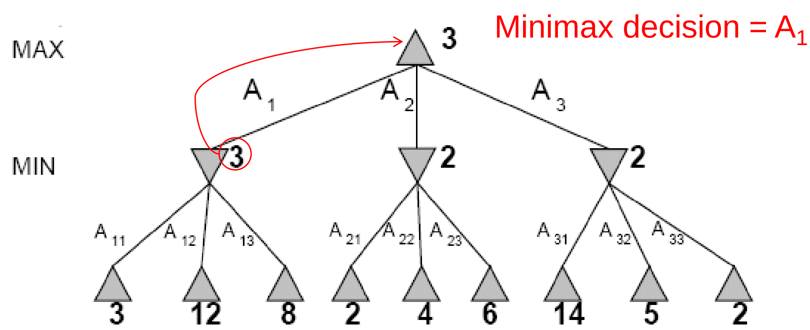
# Two-Ply Game Tree






# What if MIN does not play optimally?

- Definition of optimal play for MAX assumes MIN plays optimally

  Maximizes worst-case outcome for MAX

- If MIN does not play optimally, MAX will do even better (utility obtained by MAX will be higher). [Prove it! See Exercise 5.7]

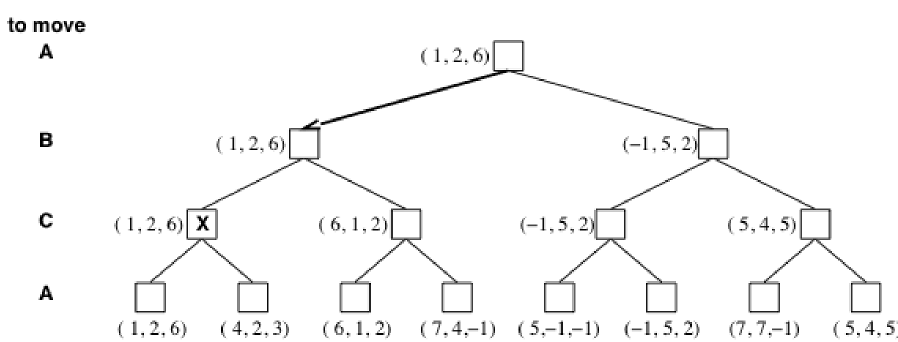
# Properties of minimax

- Complete? Yes (if tree is finite)
- Optimal? Yes (against an optimal opponent)
  Suboptimal opponents: Other strategies may do better but these will do worse for optimal opponents
- Time complexity? $O(b^m)$
- Space complexity? $O(bm)$ (depth-first exploration)



# Multiplayer Games

- More than two players
- Single minimax values become *vectors*
- At each node, apply max to appropriate component of minimax vector



# Next Time

- Alpha-beta pruning
- Heuristic evaluation functions
- Rolling the dice

**Have a great weekend!**